Continuous Probability Distributions. R

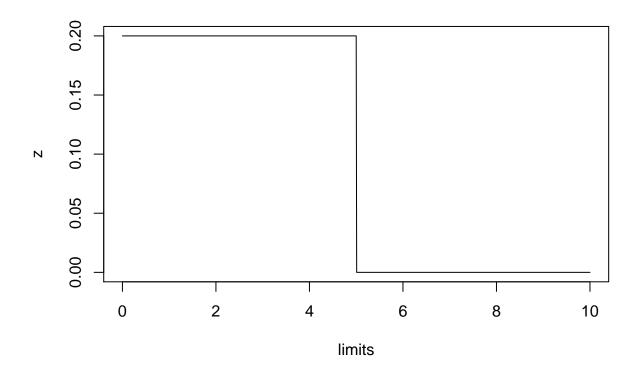
Administrator

Tue Mar 29 15:00:33 2016

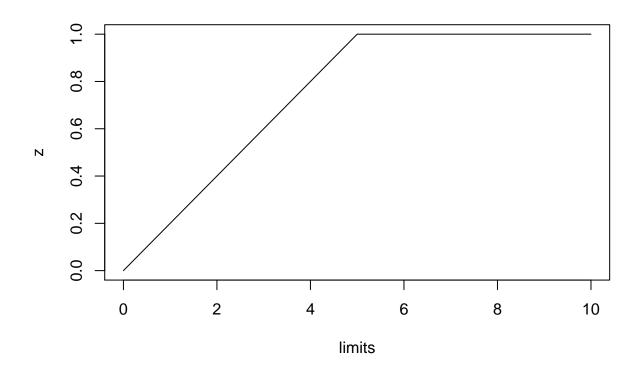
```
# Continuous probability distributions
# 24 March 2016
# NJG

# uniform
# params specific minimum and maximum

# dunif for density plot
limits <- seq(0,10,by=0.01)
z <-dunif(x=limits,min=0,max=5)
names(z) <- limits
plot(x=limits, y=z,type="l",xlim=c(0,10))</pre>
```



```
#punif for cumulative density (= tail probabilities)
limits <- seq(0,10,by=0.01)
z <-punif(q=limits,min=0,max=5)
names(z) <- limits
plot(x=limits, y=z,type="l",xlim=c(0,10))</pre>
```

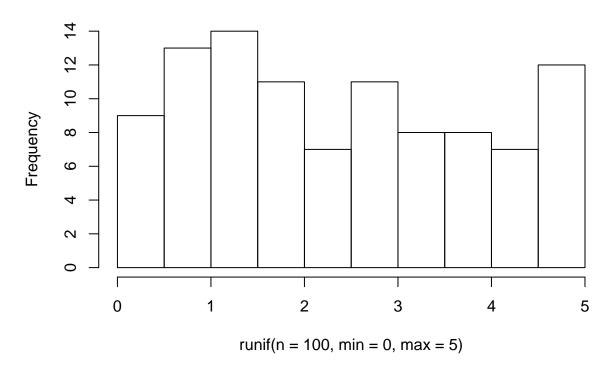


```
#qunif for quantiles
qunif(p=c(0.025,0.975),min=0,max=5)
```

[1] 0.125 4.875

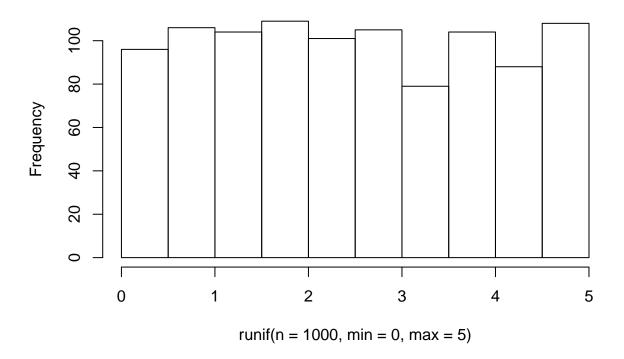
#runif for random data
hist(runif(n=100,min=0,max=5))

Histogram of runif(n = 100, min = 0, max = 5)



hist(runif(n=1000,min=0,max=5))

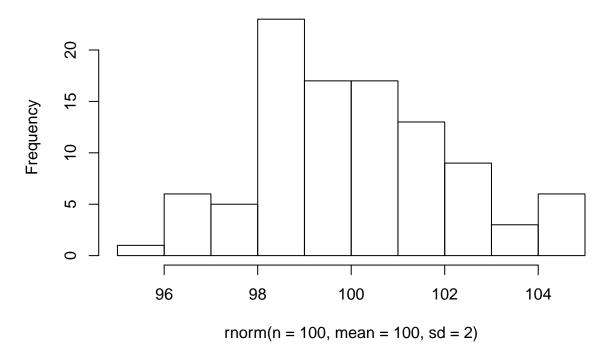
Histogram of runif(n = 1000, min = 0, max = 5)



normal

hist(rnorm(n=100,mean=100,sd=2))

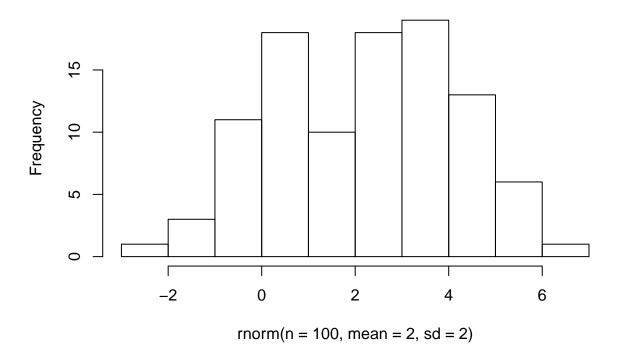
Histogram of rnorm(n = 100, mean = 100, sd = 2)



problems with uniform when mean is small but zero is not allowed.

hist(rnorm(n=100,mean=2,sd=2))

Histogram of rnorm(n = 100, mean = 2, sd = 2)

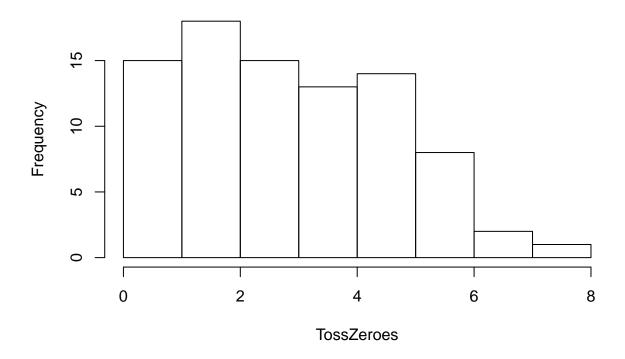


```
MyVec <- rnorm(n=100,mean=2, sd=2)
summary(MyVec)</pre>
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max. ## -1.8790 0.8296 2.1850 2.3340 4.0100 7.4190
```

TossZeroes <- MyVec[MyVec>0]
hist(TossZeroes)

Histogram of TossZeroes

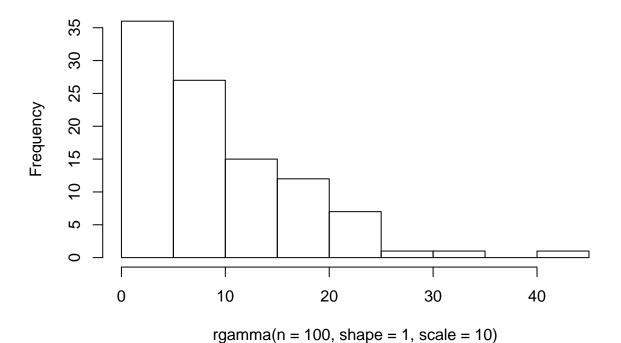


summary(TossZeroes)

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.000603 1.388000 2.625000 2.845000 4.156000 7.419000
```

```
# gamma distribution, continuous positive values, but bounded at 0
hist(rgamma(n=100,shape=1,scale=10))
```

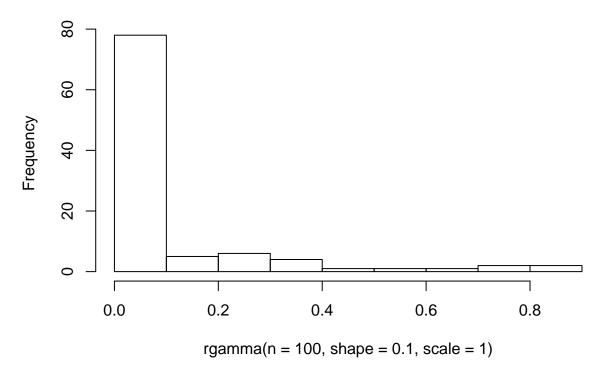
Histogram of rgamma(n = 100, shape = 1, scale = 10)



gamma with shape= 1 is an exponential with scale = mean

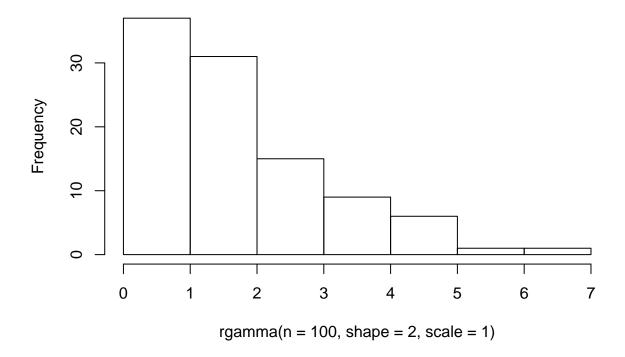
shape <=1 gives a mode near zero; very small shape rounds to zero
hist(rgamma(n=100,shape=0.1,scale=1))</pre>

Histogram of rgamma(n = 100, shape = 0.1, scale = 1)



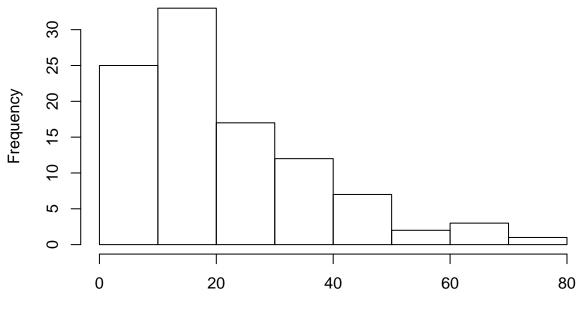
large shape parameters moves towards a normal
hist(rgamma(n=100,shape=2,scale=1))

Histogram of rgamma(n = 100, shape = 2, scale = 1)



scale parameter changes mean- and the variance!
hist(rgamma(n=100,shape=2,scale=10))

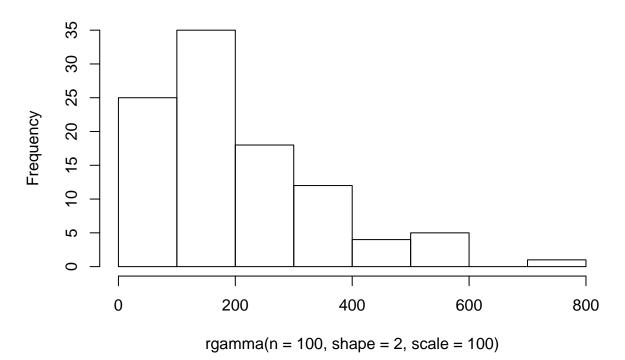
Histogram of rgamma(n = 100, shape = 2, scale = 10)



rgamma(n = 100, shape = 2, scale = 10)

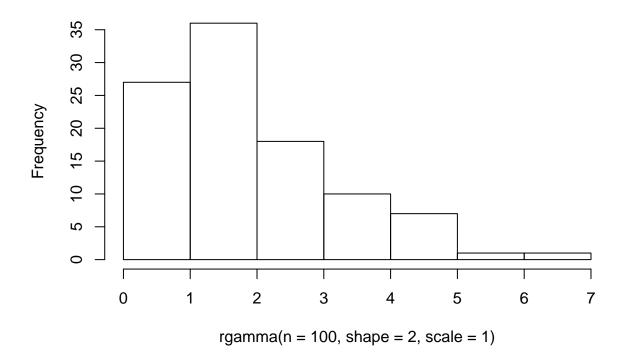
hist(rgamma(n=100,shape=2,scale=100))

Histogram of rgamma(n = 100, shape = 2, scale = 100)



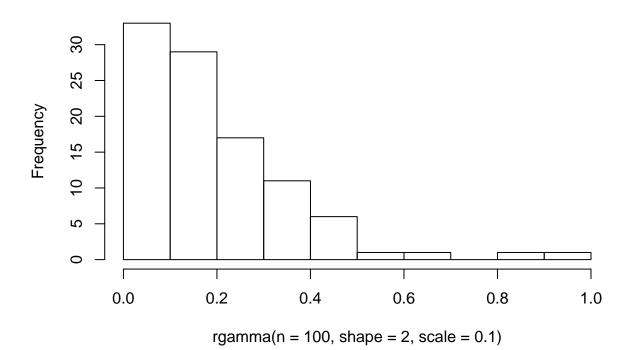
hist(rgamma(n=100,shape=2,scale=1))

Histogram of rgamma(n = 100, shape = 2, scale = 1)



hist(rgamma(n=100,shape=2,scale=0.1))

Histogram of rgamma(n = 100, shape = 2, scale = 0.1)

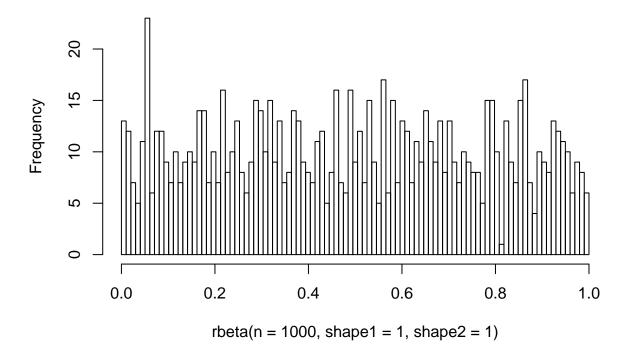


```
# unlike the normal, the two parameters affect both mean and variance

# mean = shape*scale
# variance= shape*scale^2

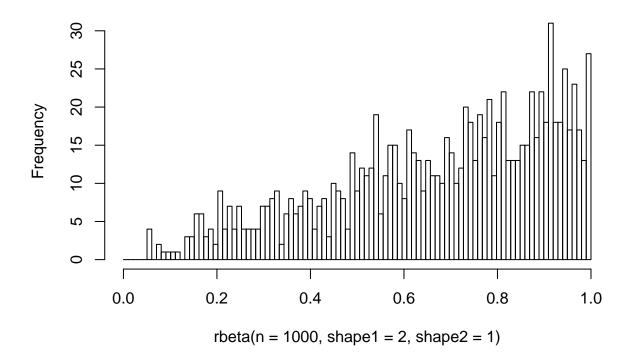
# beta distribution
# bounded at 0 and 1
# analagous to a binomial, but result is a continuous distribution of probabilities
```

Histogram of rbeta(n = 1000, shape1 = 1, shape2 = 1)



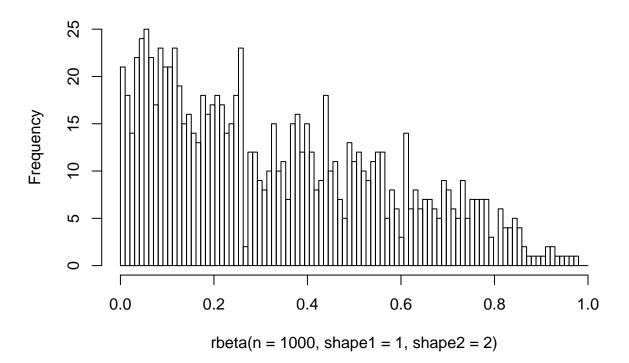
shape1 = 2, shape1 = 1 = "1 coin toss, comes up heads!"
hist(rbeta(n=1000, shape1=2, shape2=1), breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 2, shape2 = 1)



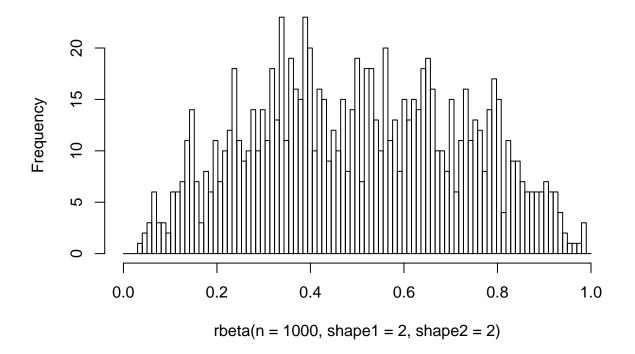
hist(rbeta(n=1000,shape1=1,shape2=2),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 1, shape2 = 2)



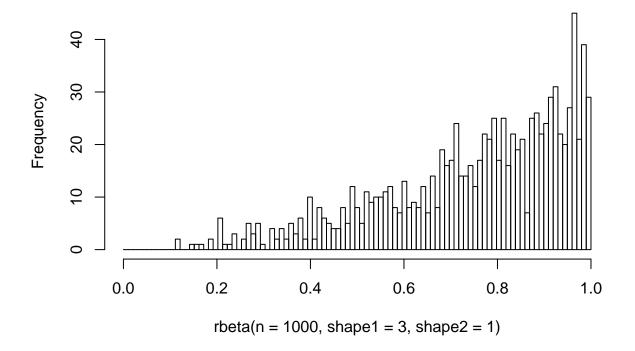
two tosses, 1 head and 1 tail
hist(rbeta(n=1000,shape1=2,shape2=2),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 2, shape2 = 2)



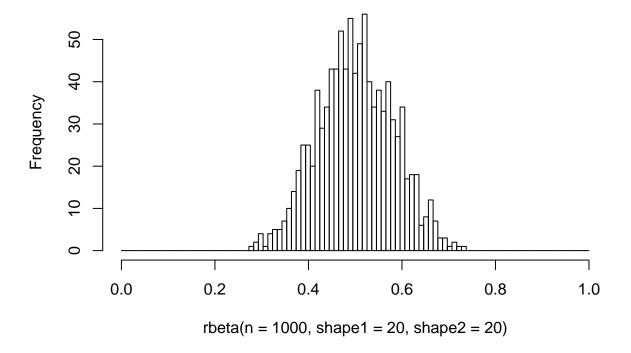
two tosses, both heads
hist(rbeta(n=1000,shape1=3,shape2=1),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 3, shape2 = 1)



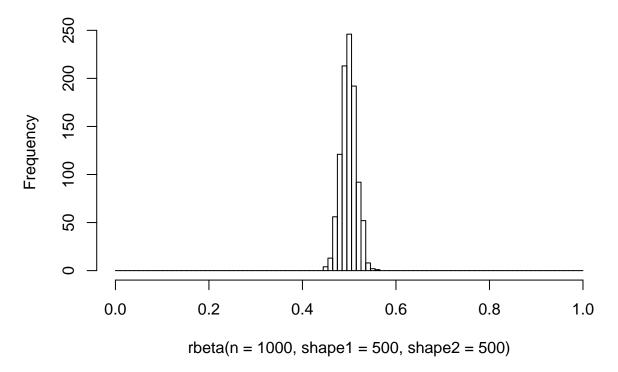
let's get more data
hist(rbeta(n=1000,shape1=20,shape2=20),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 20, shape2 = 20)



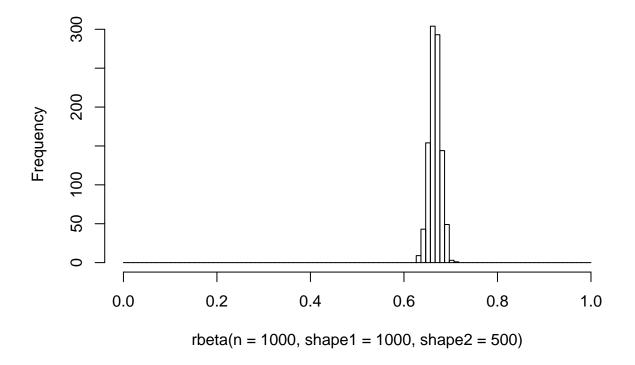
hist(rbeta(n=1000,shape1=500,shape2=500),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 500, shape2 = 500)



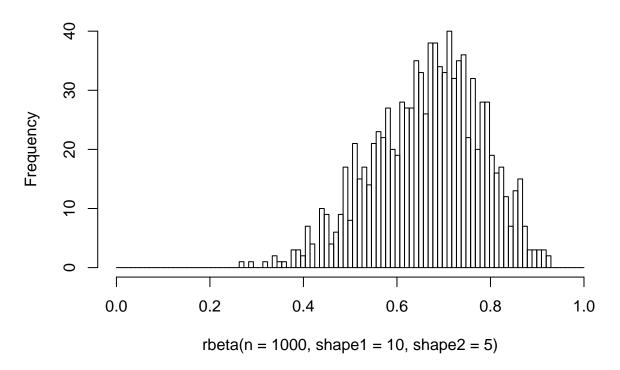
if the coin is biased
hist(rbeta(n=1000,shape1=1000,shape2=500),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 1000, shape2 = 500)



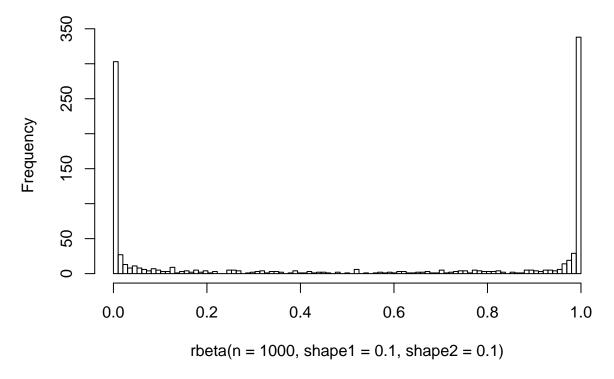
hist(rbeta(n=1000,shape1=10,shape2=5),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 10, shape2 = 5)



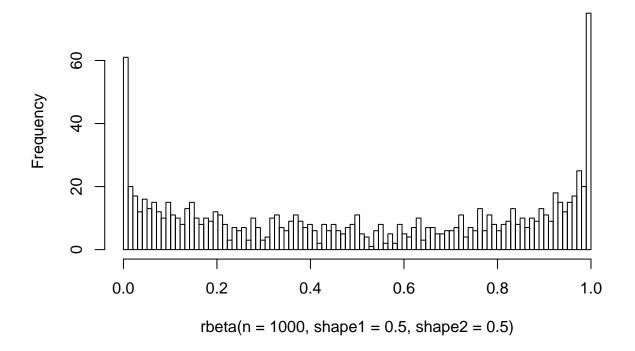
shape parameters less than 1.0 give us a u-shaped distribution
hist(rbeta(n=1000,shape1=0.1,shape2=0.1),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 0.1, shape2 = 0.1)



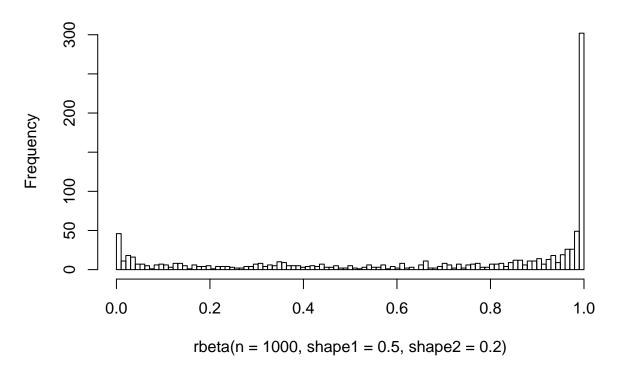
hist(rbeta(n=1000,shape1=0.5,shape2=0.5),breaks=seq(0,1.0,length=100))

Histogram of rbeta(n = 1000, shape1 = 0.5, shape2 = 0.5)



hist(rbeta(n=1000,shape1=0.5,shape2=0.2),breaks=seq(0,1.0,length=100))

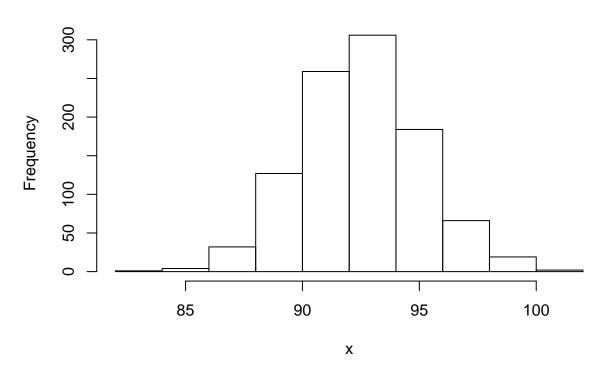
Histogram of rbeta(n = 1000, shape1 = 0.5, shape2 = 0.2)



```
# estimating parameters from data
# maximum likelihood estimator theta versus P(data|theta)

# use fitdistr function, feeding it data and a distribution type)
library(MASS)
x <- rnorm(1000,mean=92.5,sd=2.5)
hist(x)</pre>
```

Histogram of x



```
fitdistr(x,"normal")
##
                        sd
         mean
##
     92.50178159
                    2.55715063
    ( 0.08086420) ( 0.05717963)
# compare to true parameters
# compare to parameters estimated from simple means and standard deviations
mean(x)
## [1] 92.50178
sd(x)
## [1] 2.55843
# but how do we "know" what distribution to fit?
fitdistr(x,"gamma")
##
         shape
                         rate
##
     1307.2331780
                      14.1319784
    ( 58.3900244) (
                      0.6313518)
```

```
z <- fitdistr(x, "gamma")</pre>
\# find components of z
str(z)
## List of 5
## $ estimate: Named num [1:2] 1307.2 14.1
## ..- attr(*, "names")= chr [1:2] "shape" "rate"
## $ sd : Named num [1:2] 58.39 0.631
## ..- attr(*, "names")= chr [1:2] "shape" "rate"
## $ vcov : num [1:2, 1:2] 3409.395 36.858 36.858 0.399
## ..- attr(*, "dimnames")=List of 2
## ....$ : chr [1:2] "shape" "rate"
## ....$ : chr [1:2] "shape" "rate"
## $ loglik : num -2357
## $ n : int 1000
## - attr(*, "class")= chr "fitdistr"
# rate = 1/scale
# so here is the estimate of the mean
z$estimate[1]/z$estimate[2]
##
      shape
## 92.50178
# and here is the estimate of the variance
z$estimate[1]/z$estimate[2]^2
     shape
```

6.545565